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EXCESS RETURN PREDICTABILITY IN THE U.S: WHERE DOES IT COME FROM?

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| Title Excess return predictability in the U.S: Where does it come from? | | | |
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| Abstract <p>This thesis explores predictor variables and returns predictability in the U.S. market from 2001.M7 - 2018.M12. The aim is to investigate whether price-dividend ratio, earnings price ratio, variance risk premium, term spread, long-term rate of return and inflation rate explains one-month in advance excess return in the U.S during the estimation period. Predictability results are limited over a shorter horizon to avoid some complexity that comes with higher estimation frequencies. The findings in this thesis are restricted to the in-sample test and sub-period analysis. The methodology employed uses a linear factor pricing model, where these six variables are tested to justify the excess stock return.</p> <p>The primary research findings focus on the second split sample regression results, which does not include data from the 2008 and 2009 global financial crisis. It presents earnings price ratio, price-dividend ratio, and variance risk premium as one-month ahead predictor variables of excess return. The regression coefficients of these variables are statistically significant and robust in predicting excess stock return in the U.S. Among these variables, variance risk premium is the most robust predictor variable across sub-periods and models. Model 4, which is based on stepwise regression, shows that price-dividend ratio and variance risk premium account for 23% of variations of excess stock returns. Empirical results for term spread, long-term rate of return, and inflation rate show poor performance. Their regression coefficients are always statistically not significant in both the full and split-sample regressions.</p> <p>Because the findings in this work lack out-of-sample test support, it appears to be a weakness. It is, therefore, not possible to generalize these findings. Therefore, it encourages further work to determine whether to employ these variables in the U.S. and other regional markets as predictor variables.</p> | | | |
| Keywords Return predictability, predictor variables, equity premium, predictive regression. | | | |
| Additional information | | | |

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1 INTRODUCTION

A fundamental concern in financial economics is the predictability of stock return. Accordingly, there is extensive empirical research predicting excess return on stocks in the U.S. using economic variables. Typically, predictability is examined by the size of the predictive regression's coefficients and their adjusted R-square statistic (Lansing, LeRoy & Ma, 2018). Summary of previous literature reveals that U.S. stock returns have a predictable statistical and economic component called the *equity risk premium* (Campbell, 2000; Cochrane, 2007; Lettau & Ludvigson, 2009). Economic variables, including valuation ratios, inflation rate, nominal interest rate, default and term spread, and consumption-wealth ratio, forecast return as they capture fair variations in expected returns about macroeconomic risk premiums that differ over time (Rapach, Strauss & Zhou, 2009). Other researchers argue that market inefficiency and information friction are also significant in explaining predictability of stock returns (Baker & Wurgler, 2000; Hong, Torous & Valkanov, 2007; Lansing, LeRoy & Ma, 2018). The majority of current research concentrates on in-sample analyses and claim that substantial evidence of predictability of stock return exists (Stambaugh, 1999; Ang & Bekaert, 2007; Pastor & Stambaugh, 2009; Golez & Koudijs 2018).

Equity risk premium is the average return on stocks over the risk-free rate. It is relatively large and varies much more than bonds (Cochrane, 2005, p.15). The equity risk premium, also called excess return, is seen as an equilibrium compensation for risk in stocks. Though it does not directly measure risk, the underlying idea is based on the risk-return dilemma, high risk high return. Most stocks generate different levels of returns, and Cochrane (2005, p. 16) attributed this firmly to varying equity risk premium on stocks.

Since the publication of the paper 'THE EQUITY PREMIUM' (Mehra & Prescott, 1985), the dynamics of equity premium has changed completely. It has attracted huge interest from both the academic and financial industries. Their findings claim the average return on U.S stocks largely surpasses those from short-term risk-free debts more than can be rationalized by standard neoclassical models in financial economics from 1889 to 1978. Mehra and Prescott (1985) showed that the S&P 500 Index earned

an averagely 7% real annual return from 1889 to 1978 against a less than 1% average return on risk-free assets, yielding a more than 6% realized excess returns. Over the years, this central result has remained unchallenged through different data and methodologies that yield different returns. Therefore, this shows that understanding the equity risk premium is not only of academic importance but also in making everyday financial decisions.

Not only is the equity premium significantly large, but it also varies much more over time. A clear connection exists between the stock return and the underlying macroeconomic fundamentals. During bad economic times, equity premium goes up, and expected return rises because people are afraid to hold risk. Meanwhile, in good economic times, equity premium declines and expected returns fall as people are willing to take on more risk (Fama & French, 1989). It, therefore, explains significant variations in expected returns over time. Experts in asset pricing explain why equity premium varies over time by connecting it to the macroeconomy or the economics of stock returns. Macroeconomic risks are translated into financial risks, giving rise to equity premiums that vary across time based on the economic situation and across assets based on their exposure to the economy.

The predictability of excess return on stocks appears to be controversial. The reason being that different empirical studies employ different techniques, predictor variables, and data over different periods. It is the case when findings from empirical work years back change with the deployment of recent data. It contradicts and creates doubts about the authenticity and reliability of past results. Despite the shortcomings, it is certain prediction works, even with less clarity on what works. Recent studies have done nothing less but to confirm this conclusion with even other articles proposing how investors can beat the market using these variables.

Therefore, this thesis aims to examine whether price-dividend ratio, earnings price ratio, variance risk premium, term spread, long-term rate of return and inflation rate can predict a one-month in advance excess stock return. In doing so, the in-sample test is used, which addresses the following questions:

❖ Do the chosen predictors variables explain excess return in the U.S. ?

Two groups of predictor variables are used – *stock market-related* and *interest rate-related* variables – and they are expressed in monthly intervals. Stock market-related variables are price-dividend ratio, earnings price ratio, and variance risk premium, while term spread, long-term rate of return, and inflation rate are interest rate-related variables. Literature shows that both groups have a long history of excess return predictability. Analysis in this thesis is restricted to a one-month ahead predictability of excess return rather than six months or one year to avoid some of the complications that come with higher estimation frequencies. Previous studies have looked at predictability from in-sample and out-of-sample; nevertheless, the findings here are entirely on the in-sample test. A vast range of research approaches that are suggested leading to various assumptions regarding the predictability of returns is a challenge in interpreting the extensive predictability literature (Campbell & Yogo, 2006). In order to avoid this complication, the predictability method used by Lansing, LeRoy and Ma (2018) is employed to inquire whether the variables selected forecast excess return. This thesis does not attempt to establish the best model for forecasting. Instead, popularly used predictor variables in literature are considered and tested for their predictive ability on the sample data. Using more variables, only strengthens evidence of predictability.

Regression coefficients for the full sample results show that price-dividend ratio, earnings price ratio, and variance risk premium are always statistically significant across different models, implying they are a robust in predicting excess return on stock in-sample test. Because the focus is on data that does not include the 2008 and 2009 financial crisis, predictive results reveal that only price-dividend ratio and variance risk premium are robust enough to predict excess returns. The full sample regression results yield an adjusted R-square statistic of 11%, while the second split yields 23%. It means that these models explain 11% and 23% variations in the one-month ahead excess return, respectively. Empirical results for term spread, long-term rate of return, and inflation show poor performance as their coefficients are statistically never significant for neither the full nor split sample regressions.

The remaining part of the thesis goes as follows. Section 2 provides some theories on asset pricing. It also introduces some models in asset pricing. Section 3 presents empirical findings regarding the predictor variables assumed as proxies of systemic risk. A brief overview of stock return predictability is introduced in section 4. Much of the work is done in section 5. It presents the empirical study, which includes data used, methodology, findings, and analysis. Finally, section 6 conclude.

2 THE THEORETICAL REVIEW OF ASSET PRICING

Asset pricing seeks to provide understanding and explanation for the prices of assets. A high price on an asset implies a low rate of return and vis versa. In general, asset pricing explains the cross-section variability in asset returns. (Cochrane, 2005, p. 13.) Assets are anything with a promised stream of cash flows such as stock, bonds. Money is invested now with the expectation of future cash flows, which are uncertain concerning the delay and risk. Asset pricing then tries to evaluate the value of future cash flows. This process will be easy, except for delay and risk. The problem is that the delay and risk of cash flow to be realized is unknown; therefore, assets pricing is all about accounting for delay and risk. To compensate for the delay, it uses a risk-free rate; meanwhile, risk premium compensates for risk. (Cochrane, 2005, p. 13.)

A straightforward concept that gave rise to all theories in asset pricing is that the asset's price equals expected discounted payoff. Every other thing in asset pricing is an adaption or a particular case from the central concept. Two distinct approaches to this adaptation are absolute and relative pricing. Absolute pricing value assets based on their exposure to key macroeconomic risks, for instance, consumption-based and general equilibrium models. Relative pricing uses prices of similar assets to value a given asset. It makes use of little information about the asset's exposure to vital macroeconomic risks, and it is mostly used in option pricing. (Cochrane, 2005, p. 14.) Absolute asset pricing is primarily concerned with understanding and measuring aggregate or macroeconomic risk sources, which led to changes in asset price. Many analytical studies have recorded facts and connections from macroeconomics to finance. They assert that the expected returns differ in ways associated with macroeconomic variables over time and assets. In summary, asset pricing is expressed as follows,

$$P_t = E(m_{t+1}x_{t+1}) \quad (1)$$

$$M_{t+1} = f(data, parameters)$$

Where p_t is the asset's price, m_{t+1} equals the stochastic discount factor, and x_{t+1} equals the payoff from asset (Cochrane, 2005, p. 15.)

2.1 The stochastic discount factor model (SDF)

The SDF model is a technique that provides a framework that enables the pricing of assets. It is the most general and easy way to price assets. The majority of current methods of asset pricing can be seen to be SDF specific models. These include the capital asset pricing model, consumption-based CAPM, Black-Scholes option price theorem. (Smith & Wickens, 2002.) From equation (1) above, m_{t+1} is a generalized representation of SDF, implying the value of an asset today equals expectation of future payoffs. However, because m_{t+1} is a random value as we do not know future consumption, the price of an asset is estimated by taking the sum of the product of each payoff having different risk and time and the SDF. Therefore, the SDF transforms future payoffs to the present value (Cochrane, 2005, p. 1).

The purpose of asset valuation is mainly to evaluate the future stream of uncertain cash flow from an asset (Cochrane, 2005, p. 22). The value of these streams of cash flow is estimated by finding it worth to a typical investor. A mathematical equation called the utility function is used to capture what investors want and build on current and future consumption. It also captures the evident fact that people prefer money now, which is not so risky, thereby answering the question 'value to who?' (Cochrane, 2005, p. 23.)

$$U(c_t, c_{t+1}) = u(c_t) + \beta E_t[u(c_{t+1})] \quad (2)$$

$$U(c_t) = \frac{1}{1-\gamma} c_t^{1-\gamma}$$

$$U'(c) = C^{-\gamma}$$

As γ turns to 1, $U(c) = \ln(c)$

Where c_t equals today's consumption, c_{t+1} equals tomorrow's consumption, β equals the discount factor, and $u(c_t)$ and $u(c_{t+1})$ are utilities of consumption today and tomorrow, respectively. The above utility function captures the fundamentals of an investor, which is the desire to consume more, and after a certain quantity, the

additional unit does not give the same satisfaction as the first. (Cochrane, 2005, p. 23.) Investors maximize this function by allocating their wealth optimally between consumption and investment (Suomala, 2013). A typical and very convenient way to express the utility function is through the power function (3),

$$\max u(c_t) + E_t[\beta u(c_{t+1})] \quad (3)$$

$$c_t = e_t - p_t \xi,$$

$$c_{t+1} = e_{t+1} + x_{t+1} \xi$$

First-order condition for optimum allocation of investor's wealth to consumption and investment is obtained by replacing the constraint with the objective function, differentiating for ξ and then equating it to zero as shown below,

$$P_t u'(c_t) = E_t[\beta u'(c_{t+1})x_{t+1}] \quad (4)$$

or

$$P_t = E_t\left[\beta \frac{u'(c_{t+1})}{u'(c_t)} x_{t+1}\right] = E_t\left[\beta \left(\frac{c_{t+1}}{c_t}\right)^{-\gamma} x_{t+1}\right] \quad (5)$$

In equation (4), $P_t u'(c_t)$ refers to the amount of utility lost for a unit increase of an asset, while the other half $E_t[\beta u'(c_{t+1})x_{t+1}]$, refers to increased (discounted) utility from additional payoff at time $t+1$. Investors obtain an optimum allocation of his wealth between consumption and investment when marginal loss equals marginal gain. When equation (4) is expressed in terms of the asset price, it gives rise to equation (5). This formula constitutes the central formula in asset pricing and the foundation from which most theories and the formula in asset pricing come from. (Cochrane, 2005, p. 24.)

Equation (5) is considered the basic equation for pricing assets and also called the consumption-based model. It represents the basic formula from which all other asset pricing formula is derived. It was first developed by Lucas (1978). For a better understanding of this equation, a convenient way to break it up is by defining the SDF m_{t+1} ,

$$m_{t+1} = \beta \frac{u'(c_{t+1})}{u'(c_t)} \quad (6)$$

The basic equation for pricing assets is written as,

$$P_t = E_t(m_{t+1}x_{t+1}) \quad (7)$$

$$P = E(mx)$$

2.2 The consumption-based capital asset pricing model (CCAPM)

The peculiar feature in basic equation in asset valuation, as seen above, is that asset's price and return are connected to the investor's decisions about consumption and savings (Suomala, 2013). The CCAPM, developed by Breeden (1978), is a practical application of the fundamental equation in asset pricing. The model employs data on consumption in estimating asset returns. It expresses a linear connection between consumption growth rate and asset's return from the model (Elton & Gruber, 1991, p. 322).

The CCAPM is built under several assumptions. Breeden assumed:

1. All assets with risk can be traded.
2. Investors' beliefs are the same.
3. There is no cost involved in trading other assets.
4. The returns of assets follow the Ito process (Suomala, 2013).

It is represented as follows,

$$R_{it} = \alpha_i + \beta_i C_t + e_{it}, \quad (8)$$

Where R_{it} is asset return, C_t refers to aggregate consumption growth rate per capita, α_i equals constant term, and e_{it} equals residual term (Suomala, 2013). Beta is represented from this model as,

$$\beta_{it} = \frac{Cov(R_{it}, C_t)}{Var(C_t)} \quad (9)$$

The model is appealing and straightforward when expressed in this form. It is an ideal way to calculate expected returns without losing the fundamental principle that makes up the theory. With all the studies on this model, there is no empirical evidence to support it. Therefore, the CCAPM does not work in practice. Breeden's model and the original model by Lucas have undergone several tests through studies, but none seem to be supported empirically. (Suomala, 2013.)

The equity premium puzzle lacks explanation from the consumption-based models (Mehra & Prescott, 1985). In the past 90-years period, the US equity risk premium has been about 6% while their standard deviation over 16%. Over the same period, the per real capital consumption average growth rate was less than 2%, with a standard deviation of about 4%. It shows that the variation of consumption growth concerning stock returns is little at explaining the enormous risk premium that accompanies equity securities (Mankiw & Zeldes, 1991). Lucas model can only explain the enormous risk premium under extremely high aversion parameters, meaning the model does not work correctly in practice (Suomala, 2013).

Like any other study, empirically testing consumption-based models pose its own difficulties that mostly link calculating per capita consumption growth rate (Suomala, 2013). Breeden, Gibbons and Litzenberger (1989) studied the implications from the Breeden (1978)'s CCAPM, and reported 4 econometrics issues that relate to the consumption estimate: (a) statistics used are on reported expenditure not on consumption, (b) there is less frequent reporting of consumption data compare to stock returns, (c) total expenditure is reported in the statistics rather than expenditure at each time and (d) there are errors from sampling in the data. (Suomala, 2013.) These limitations pose a problem and can cause bias in the estimated result.

Using the international stock market, Cumby (1990) test the consumption-based model. He studied whether it can explain stock return in four different countries. Countries used here are the US, UK, Germany, and Japan. From his studies, he claims the consumption-based model lacks a full explanation of real stock returns.

An additional limitation of the CCAPM is the way the risk of assets is measured. It is done differently from the ways of investors - that is, calculating the covariances of

investors exogenous variables. The meaning of Exogenous variables here refers to variables that are independent of investment decisions. Consumption is endogenous of investors' decisions; therefore, CCAPM fails to represent the way investors perceive risk correctly. (Suomala, 2013.)

Even with all these limitations, consumption-based models still hold the necessary functionality in financial economics. Empirical studies that fail to support the model should be interpreted against the specific functionality of the model rather than the whole model because other models represent specific versions of the original consumption model and not an alternative. (Suomala, 2013.)

2.3 The capital asset pricing model (CAPM)

CAPM is first and by far, the most popular and commonly used model for asset valuation (Cochrane, 2005, p. 152). The model was established by Sharp (1964), and Linter (1965). CAPM ties the return of a wealth portfolio to its discount factor (Cochrane, 2005, p. 152). It is expressed as a linear function,

$$m_{t+1} = a + bR_{t+1}^W, \quad (10)$$

It is often expressed as follows,

$$E(R^i) = \gamma + \beta_{i, R^W} [E(R^W) - \gamma], \quad (11)$$

CAPM's extensive use in finance is because of its simplicity to estimate asset returns and risk premiums. Though the CAPM came to existence earlier than the consumption-based model, it remains a derivative of the consumption-based model. It estimates the risk of an asset by covariating a return on an asset with that of the market. (Cochrane, 2005, p. 171.)

$$E(R^i) = R^f + \beta [E(R^m) - R^f], \quad (12)$$

The above formula indicates that expected return $E(R^i)$ equals risk-free government debt plus beta multiply by risk premium. Portfolio from the market, less a rate on risk-free government debt equals the market premium (Chen, 2003). The beta is calculated as follow,

$$\beta = \frac{Cov(R^i, R^m)}{Var(R^m)} \quad (13)$$

From the formula, β is the covariance of assets and market returns, expressed over the variance of market returns (Cochrane, 2005, p.171).

CAPM stipulates that the return on an asset is driven by its systemic risks expressed as β , which estimates the responsiveness of the return of an asset to the market. Higher β means asset return is more sensitive to market movements and vis versa — higher beta results to higher expected returns. The fundamental idea in CAPM remains the same as that of the consumption-based model but different in the way the systemic risk is measured and the kind of data utilized. The CAPM uses market returns data, whereas the consumption-based model uses data on consumption. (Cochrane, 2005, p. 171.)

Like any other model, CAPM has strong underlying assumptions, some of which are reasonable, but most are challenging to describe financial markets. The assumptions are

1. The absence of transaction cost.
2. Assets can be divided without limit, and individual transactions do not affect prices.
3. Investors can short sell without limit and lend without charge at risk-free rate.
4. Assets are tradable, including human capital.
5. Investors' decisions are based on the portfolio's expected return and standard deviation.
6. All investors have equal expectations for the future.

(Elton & Gruber, 1991, pp. 284 – 285.)

Most models are based on simple assumptions that help describe complicated realities. Though the CAPM has many unrealistic assumptions, it should not be judged based on this; rather, it should be judged based on its predictability power. Two assumptions form the basis of CAPM (a) market portfolio is mean-variance efficient, and (b) risk-return tradeoff is accurately represented using the security market line. The mean-variance efficiency means the differences in assets beta explains the variation in expected returns across securities. (Suomala, 2013.) Because the market portfolio is not observable, this creates problems in testing CAPM; therefore, the market portfolio need to contain asset trading in the market, but it's not the case. To address the issue, CAPM uses equity indices to proxy the market portfolio. (Suomala, 2013.)

CAPM does not have an encouraging empirical record. Cross-sectional regression studies reveal the relation between beta from the market, and the expected return of assets is entirely unexplained using CAPM beta. Further time-series test by Blume and friend (1970) also confirms CAPM's lack of empirical evidence. In the case where CAPM holds, assets betas are the sole effect of asset return variation. Nevertheless, there are other factors with empirical evidence of asset return variation other than asset betas. Therefore, there exist other factors besides the market beta that helps explain the phenomenon. (Suomala, 2013.)

2.4 The intertemporal capital asset pricing model (ICAPM)

ICAPM is a pricing model focused on consumption and provides the expected return on an asset. The expected return relies not only on the covariance with the market but also on state variables which, reflect the movement of investment opportunities. (Bali & Engle, 2010.) Cochrane (2005, p. 184) used a linear model of wealth and state variables to predict shift in potential return distribution. ICAPM was first suggested by Merton in 1973. It's an expansion of CAPM and often allows for variables that change over time. Many multifactor models are developed due to the limitations of CAPM, such as size, value, and momentum anomalies. Merton (1973) claims that many of these models are derivatives and applications of ICAPM. Fama (1991) even went ahead to called it the fishing license, making some author say the ICAPM

provide the risk factors used in their model with some theoretical foundation. ICAPM assumes creditors may attempt to hedge their risky investments based on actual and expected variables such as inflation, potential returns, and unemployment rate. It utilizes a mean-variance model to achieve distribution overtime for the risk of consumption. It spans several periods and uses several beta coefficients to compensate for the different investments in hedging. ICAPM develops a model with linear discount factors that are then used as the state variables in decision making regarding the investor's consumption portfolio. These variables estimate the investor level of achievement when in full maximization.

$$M_{t+1} = a + b'f_{t+1} \quad (14)$$

This model considers current wealth a state variable and that more state variables go a long way to explain the investor's future return distribution better. It also considers relative price changes as a state variable in the case of an international model. (Cochrane, 2005, p. 184.) Based on Maio and Santa-Clara (2012), ICAPM express risk-return equilibrium relation as,

$$E_t(R_{i,t+1}) - R_{f,t+1} = \gamma Cov_t(R_{i,t+1}, R_{m,t+1}) + \gamma_z Cov_t(R_{i,t+1}, \Delta z_{t+1}) \quad (15)$$

Where the risk-free rate is $R_{f,t+1}$, the return on the asset is $R_{i,t+1}$, the return on the market is $R_{m,t+1}$ and the change in state variable equals Δz_{t+1} (Maio & Santa-Clara, 2012). Although state variables are not defined explicitly by ICAPM, some constraints must be met by such state variables. Firstly, state variables should be able to predict either the first or second moment of stock return. Secondly, if an individual variable specifies the predicted positive returns, the innovation will produce a positive risk in cross-section experiments, whereas the variables that predict negative outcomes will obtain a negative risk. Thirdly, as an approximation for the relative risk aversion to the representative investor, the market price derived from the cross-study must be economically feasible. From the above equation, the second term $\gamma_z Cov_t(R_{i,t+1}, \Delta z_{t+1})$ form the connection between ICAPM and standard CAPM. If $\gamma_z = 0$, the original equation becomes the standard CAPM forming the basis for many

multifactor models and the reason why the Fama (1991) called it a fishing license. (Maio & Santa-Clara, 2012.)

ICAPM and CAPM vary primarily from each other in terms of additional state variables, which accept that investors protect themselves from changes in potential investment opportunities. The model is flexible in that, of course, effects other than the change in the investment opportunity can be generalized to include in an obvious way. Wage levels and other consumer goods whose relative prices vary with time are two significant factors not taken into account (Merton, 1973). Although ICAPM acknowledges the significance of risk factors in finance, it does not thoroughly identify the risk factors and how they affect asset price measurement.

2.5 The arbitrage pricing theory (APT)

APT is CAPM's substitute, developed by Ross (1976). It aims at explaining the cross-sectional variability of asset's return. APT is founded on three main principles: (a) factor models can be used to describe asset return, (b) enough securities are available to mitigate idiosyncratic risk, and (c) efficient markets oppose arbitrage opportunities to be persistent. The factor model is a type of pricing model estimating the returns of assets as a linear function of factors. For the second principle, since there are enough securities to diversify firm-specific risk, they cannot generate excess return. An arbitrage opportunity is the ability to make a riskless profit without any increase in net investment. Arbitrage pricing theory claims that an efficient security market prevents arbitrage opportunities or immediately wipe them off if they exist. (Suomala, 2013.) The SDF is defined by each pricing model differently. Below, Cochrane (2005, p. 193) shows how the factor pricing model define SDF a linear function of a set of proxies,

$$m_{t+1} = a + b_A f_{t+1}^A + b_B f_{t+1}^B + \dots, \quad (16)$$

Where a , b are parameters and f^i are factors. Future cash flows are converted to value by the stochastic discount factor (SDF). It does the same thing as in earlier discussion. The SDF is defined as an investor's marginal utility under the original

consumption-based model, while factor considered proxies of marginal utility under the factor models, the model is demonstrated as follows,

$$\beta \frac{u'(C_{t+1})}{u'(C_t)} = a + b_A f_{t+1}^A + b_B f_{t+1}^B + \dots, \quad (17)$$

When put in a form to explain returns, the factor pricing model looks as follow,

$$R^i = E(R^i) + \sum_{j=1}^M \beta_{ij} f_j + \varepsilon^i \quad (18)$$

Where $E(R^i)$ is an asset's expected return, β_{ij} are betas; f_j are factors, and ε^i is the residual. The asset sensitivity to risk is estimated by β , while factors measure price of the risk. The model indicates that the return on an asset equals expected return and sum of random return - idiosyncratic return plus factor return. Factor return measure systemic risk, and in case the factor is zero, asset return equal expected return of the asset plus random return specific to the firm. Since the idiosyncratic return is uncorrelated and has zero mean, they can be avoided by forming a well-diversified portfolio, and therefore, it is not rewarded. On the other hand, factor risk is unverifiable, and factor pricing model claims that an asset return depends on their sensitivity to systemic risk factors. (Suomala, 2013.)

APT identifies no factor. Instead, it is empirically gotten when data is used to get the best fit of a linear model. Three different categories of factors exist statistical factors, fundamental factors, and macroeconomic factors. The best proxies for marginal utility is the macroeconomic factors. They are intuitive and straightforward and include variables such as change in industrial production, inflation, or interest rate. Meanwhile, fundamental factors include dividend yield, firm size, or book-to-market ratio; therefore, they link to the company. (Suomala, 2013.)

Empirically, factor pricing models are estimated in two ways, either by running cross-section or time series regressions on the data. Most commonly, cross-section regression is used, and returns are estimated using the expression,

$$E(R^{ei}) = \gamma + \beta_i \lambda_a + \beta_i \lambda_b + \cdots + \alpha_i, \quad i = 1, 2, \dots, N, \quad (19)$$

Where α_i are pricing errors, and γ is the intercept. CCAPM, CAPM, and APT constitute pricing models aimed at explaining the risk-return tradeoff. Empirically, CCAPM and CAPM could not explain this relationship. The only alternative to these two models is the APT, whose empirical usefulness is due to its cross-sectional ability test in cases of more than one factor. (Suomala, 2013.)

3 PREDICTOR VARIABLES FROM EMPIRICAL STUDIES

Due to intangible empirical evidences of CAPM being unable to explain the return of an asset, alternative pricing models developed to address this issue. Certain empirical studies have contradicted what CAPM beta stands for. They claim stocks having low beta have reported higher return, and stocks having high beta have reported low return (Black, Jensen & Scholes, 1972; Blume & Friend, 1973). Therefore, this means systematic risks that drive returns on stocks are unable to be explained entirely by CAPM beta, and therefore, the need to account for more risk factors. A continuous research in finance has given rise to better measures of systematic risk beside CAPM beta. Studies show that smaller firms have reported high risk-adjusted return (Banz, 1981). Other studies on firms with a high earnings-price ratio have reported a similar outcome (Basu, 1983). The issue with CAPM beta is, therefore, it's inability to explain either of these observations. Research in finance has identified some macroeconomic variables to be predictors of stock returns. Inflation, industrial production, valuation ratios, and changes in interest rate spread are identified as significant predictor variables of stock expected returns (Chen, Roll & Ross, 1986.) Other studies claim patterns in stocks and bonds return are explainable by interest rate-variables such as term spread and default spreads (Fama & French, 1989).

3.1 The effects of value and size factors on stock return

Limitations of CAPM encourage advanced research in finance, which result to the development of new models. Early research by Banz (1981) and Basu (1983) created the framework for developing Fama and French (1993) three-factor model. The model uses three factors as predictors to explain stock return. Beside market excess return, the model also uses value and size effects.

3.1.1 The effects of value and size factors

A critical study on size effects was done by Banz (1981). He studied the connection between NYSE stock returns and market values. He has an observation period of 40

years, from 1926 to 1975. He employed the fundamental pricing model to estimate stocks expected return as function of market return plus an additional factor. He then concluded that CAPM is misspecified. Empirical evidence shows that averagely, smaller firms provide risk-adjusted returns that are significantly larger than larger firms throughout estimation. The result is reliable for smaller firms and less significant for average to large size firms. He made available no reasons for the outcome nor explain whether it's due to size or other factors that correlate with size.

In a later study Basu (1983) empirically examines the association between returns on NYSE stock, earnings yield, and firm size. He concluded that risk-adjusted return for higher earnings-price ratio stocks is more significant than low earnings-price ratio stocks. A high earnings-price ratio means stocks are undervalued about their earnings.. When return accounts for differences in earnings-price ratio and risk factors, the size effect practically disappears. Based on this, Basu believes both size and earnings-price ratio are unable to explain the expected return; however, they can be considered proxies' determinants of stock's expected return.

Rosenberg, Reid and Lanstein (1985) did another vital study, examining the connection between stock return and book-to-price ratio (BP). BP ratio expresses the connection between a stock book and market value. Value stocks have a high BP ratio, whereas growth stocks have a low BP ratio. Rosenberg's study uses return of stocks quoted on NYSE, ASE, and NASDAQ between 1973 – 1984. From his findings, he claims a positive association exists between stock return and the high BP ratio, and that value stocks provide higher return on average.

Another critical study, Fama and French (1992), empirically tested the cross-section variability of return in the U.S. Five different underlying risk indicators are used; market beta, size, the E/P ratio, book-to-market equity, and leverage. It shows all the factors have significant explanations except for market beta; however, leverage and E/P are non-significant when the size and BP are used. Meaning that size and BP explain better the cross-sectional variability of stock return on Amex, NASDAQ, and NYSE between 1963 – 1990.

After the study by Fama and French (1992), they expanded it to Fama and French (1993). Here they examined the cross-sectional variability of return, stock return, and went further to explain bond return. Fama and French (1992) claim size and the BP ratio explain cross-sectional variability of stock return. In an attempt to explain bond return, they added to the study two interest rate variables; term spread and default spread. The methodology used in the study incorporates that of Black, Jensen, and Scholes (1972). At the end of their study, they created the famous three-factor model, that has excess market return, size and value as risk variables. Spread between return of a small stock portfolio and that of big stock portfolio indicate the size factor. It is also represented as SMB. Spread between the return of value and growth stock portfolio indicates the value factor. It is expressed as HML. The model is expressed as follows,

$$R_t^M - R_t^f = a + b[R_t^M - R_t^f] + sSMB_t + hHML_t + e_t \quad (20)$$

Where a is the intercept, $R^M - R^f$ is excess market return, and e_t is firm residual. Fama and French analyze their study by using size, and BP ratio to sort stocks into five quantiles, which then results in 25 sub-portfolios with the estimated excess returns. These portfolios' SMB and HML are examine to verify if they capture similar features in stock return that are connected to size and value.

The findings from Fama and French (1993) hold that excess market return, size and BP ratio have an adequate explanation for the cross-sectional variation of stock return. The regression's intercepts are close to zero. Moreover, the sub-portfolios R-squared lies in the range of 0.83 – 0.97, meaning the model captures a significant variability in the sub-portfolios. HML and SMB alone capture a big fraction of the variation regardless of other variables in the regression. The excess market return factor explain the spread between average stock return and one-month government debt.

After Fama and French (1993), so many researchers focused on proving their validity. Most research questions expressed concerns whether size and value factors firmly explain cross-sectional return in other markets besides the U.S. Fama and French (1998) attempt to prove this by studying the average return of international portfolio

containing high and low book-to-market equities between 1975 – 1995. Out of the thirteen significant markets, twelve of the value stocks outperform the growth stocks. To confirm robustness of these factors, Barry, Goldreyer, Lockwood and Rodriguez (2002) explore the effects of these factors on emerging markets from 1985 to 2000. They adapt their method to the emerging market by defining size and value to the individual firm's market average. Their research claim value stocks have significantly higher return than growth stocks, and small stocks' return exceed those of large stocks, though they lack the robustness because extreme returns were removed. Another empirical study by Drew and Veeraraghavan (2002) further supports prevalence of size and value premium in other markets. Their research is focused on understanding cross-section returns in Malaysia from 1992 to 1999. They claim the three-factor model offer an economically meaningful explanation for stock return in Malaysia.

Other studies fail to accept the three-factor model in other markets. Griffin (2002) examine if the global version or country-specific of SMB and HML offer good explanation for the variation of stock return over time. His result confirms the use of country-specific versions, but fails to support the global versions' ability to explain stock return changes over time. Mirza and Afzal (2011) provided a similar conclusion after evaluating the European market model's performance. Their study includes stocks from 15 European markets and, as a difference from other studies, uses daily return between 2002 – 2006. The model fails to explain 5 out of 6 portfolios under investigation, and therefore, they join Griffin (2002) to conclude that it provides poor performance for the global portfolio.

3.1.2 Interpretation of value and size factors

Due to the Fama French three-factor model's tremendous performance, there are debates on how size and value factors are interpreted economically. There are several controversies about the explanation of these concepts. According to Fama and French (1992), higher return attracted by small and value stocks in a rational market compensate for higher risk. Meaning in a market full of systematic risk, size, and value are proxy for these risks. They also claim that size and value are connected to the underlying concepts of the economy. Businesses that are not doing good have a higher

discount rate, which results in lower prices. It could be seen from the firm's high book-to-price ratio and expected return. They also show high book-to-price ratio firms have lower earnings than low book-to-price ratio firms. In terms of size, Fama and French claim that smaller firms are more vulnerable to financial distress compared to larger firms, and this makes them riskier. Liew and Vassalou (2000) also show strong support for Fama and French explanation for these factors. They used data from 10 countries to show size and value embed much information on future GDP growth and are proxies of fundamental risk measures.

Besides the risk-based explanation for this phenomenon, there are other explanations. According to Lakonishok, Shleifer and Vishny (1994), high return from value stocks does not come from higher risk instead of the inefficiency of the market. They claim higher book-to-price ratio stocks get higher return reason being, investors are irrational and fail to evaluate a firm's past earning growth rate. Investors are pessimistic about firms that exhibit poor performance in their history and optimistic about those that did well. Another explanation is that growth stocks seem to be glamorous and appealing to naïve investors than value stocks, which cause them to drive prices up and lower expected return. Daniel and Titman (1997) also did not accept the risk-based explanation. They suggest the higher return on stocks could be coming from somewhere other than higher risk. It could be from firms that have a high BP ratio, and is in related line of business, the same industry, or from the same region. At least these are the characteristics that drive returns, and not the covariances of systemic risk factors.

3.2 Risk factors from the macroeconomy

As for indicators of systemic risk, many asset pricing models use macroeconomic factors. These models connect asset returns to the underlying economic fundamentals. Because economic conditions and aggregate consumption are related, they indicate how an investor feels. Macroeconomic factors indicate the business condition of an economy; therefore, expected excess return is linked to future macroeconomic factors. Many variables are direct tests of the present economic

condition: Inflation rates, industrial production, and GDP shifts. Other consideration includes financial variables that are indicators of anticipated market conditions and thus valuable factors for systemic risk assessment.

Term (TERM) and default (DEF) spreads are two financial variables that are commonly used to explain risk premiums. The disparity between government bond rates for long and short-run, is term spread, while default spread is the disparity between the yield on the long-run corporate bond and that of long-run government bonds. Because the term structure of interest rates is measured using term spread, it is also possible to use term spread to graphically express the premium on long-run bonds compare to short-run bonds in what is called the yield curve. Besides using term spread to demonstrate investors' compensation for investing in long-run risky bonds, they are widely used predictors of real economic activities. Future economic growth increased consumption, affordable consumer goods, including investment, are suggested as positive term spread and upward gradual yield curve. Contrarily, a downhill curve indicates a potential recession.

The default spread of a company is determined by the difference between its borrower interest rate and rate on risk-free asset. The impact of default on equity return has been studied in several studies. The emphasis of these studies was the ability to explain return by the default spread. However, several of these studies indicate that much of the default information is not linked to the default risk. In support of this phenomenon, the default risk is correlated with macroeconomic conditions and relies on the business cycle. Denis & Denis (1995) claim default risk and macroeconomic factors are related and change alongside business cycles. Elton, Gruber, Agrawal and Mann (2001) estimate that much of the corporate bond risk premiums is compensation for systemic risk holding. Vassalou and Xing (2004) show that in their cross-section of equity return, default risks are systematically priced.

Two systemic risk measures commonly used are term and default spread. They are empirically supported to be used in pricing models to explain return. In addition to financial variables like term and default spreads, Chen, Roll, and Ross (1986) studied some macroeconomic variables to understand whether they are predictor variables. They used a model of asset pricing that include many macroeconomic risk factors to

estimate monthly excess stock return. These factors are assumed to affect returns on stock systematically. The period for study is 1953 – 1983, and the risk factors used are the monthly and annual growth rate in industrial production, term spread, default spread, changes in expected inflation, and unexpected inflation. In addition to this, they developed a model that adds a stock market component, which could either be the return from an equal or value-weighted NYSE index.

Using model they developed, their findings show that macroeconomic variables are robust predictor variables over the estimation period. All variables used are statistically crucial except for the industrial production's annual growth rate. Term spread is marginal, whereas default spread is statistically significant over the entire period. One unique finding of the work is the effect equity factors have on the model. Equally or value-weighted returns did not show any significant effects in pricing in any subperiod. Market return factors neither impaired the statistical significance of macroeconomic factors. To conclude, returns from stocks are sensitive to economic news, and returns are estimated based on their degree of exposure to systematic risk (Chen, Roll & Ross, 1986).

Fama and French (1989) did a study which complements the evidence Chen, Roll, and Ross (1989) got for a cross-section of stock return. Their research focuses on predicting stock and bond return using default spread, term spread, and dividend yield. They equally investigate whether business conditions are the cause of variation in expected returns. The period underestimation is between 1927 – 1987, and the return underestimation is those from NYSE value and equally weighted portfolios. The study shows that long-term bonds and common stock returns have a maturity premium with a trend for the market process. The expected return goes up during bad business conditions and down during good business conditions.

Fama and French (1989) show term and default spreads as business conditions. Their findings reinforce Chen et al. (1986) argument on default spread, which claims stock returns are influenced by the covariance between default spread and stock return. They also show that return variation caused by default spread is bigger for stocks than for bonds, same for smaller stocks than for larger stocks. They claim default spread

and dividend yield are highly correlated and that these two variables are long-term indicators of business condition. Throughout the study, default spread and dividend yield were low during good economic times and high otherwise. (Fama & French, 1986.)

While Fama and French (1986) show default spread to be a long-run business condition, they also claim term spread is a short-run business condition. The term spread is higher towards business cycle troughs and lows towards the peak, result in their characteristics. Yields of long-term bonds increase less than short-term debt securities in good economic times and decrease less in bad economic times. Therefore, term spread follows the business cycle pattern.

Fama and French (1986) expanded their findings with two explanations of why expected return changes with business cycles. The first being consumption soothing, and the second, risk premium variation. Consumption smoothing arises due to higher income compared to wealth, causing investors to smooth future consumption through increase savings. On the other hand, when income is low, investors are less willing to save. Without any changes in investment opportunities, reduced savings result to fall in asset prices, resulting from the increasing expected return. This phenomenon of variation of the expected return with business cycles is consistent with SDF and CCAPM by Lucas (1978). The second explanation is that investors' perspective towards risk changes with business conditions. Risk tends to be higher during poor business conditions and low during good business conditions; thus, default and term spreads are strong systemic exposure proxies.

Fama and French (1993) is another study where they test default and term spread as risk factors. They used these variables in work, where they develop the three-factor model. Their work was to investigate whether the same variables that predict stock return also predict bond return and vis versa. The result shows that most of the variations in bond return are captured by term and default spreads. One exciting feature of these two factors is that they also capture substantial variations in stock return when used alone in time series regression. Fama and French later develop a model that uses these two factors to explain excess return of the 25 portfolios created

based on their size and BP ratio. For 25 sub-portfolios in regression, both term and default spread are statistically significant. Fama and French noticed the parameter estimate for the 25 stock portfolios is similar to those of long-term bonds; therefore, long-run bonds and stocks are sensitive to risk capture in term spread. Default spread for small stocks exhibits higher t-values and lower t-values for large stocks. Fama and French (1993) also claim return of small stocks is sensitive to default spread than that of large stocks. Besides all these, the R-squares of the 25 sub-portfolios are lower than the R-square values for bond portfolios. R-square values for stock portfolios were 0.06 – 0.21, while those of bond portfolios were around 0.49 – 0.97. It, therefore, mean term and default spreads only explain a small fraction of cross-section variability in stock return even though they are statistically significant. Another regression where SMB and HML are used along with the term and default spreads still shows a less significant R-square. Therefore, term and default spreads are unable to enhance a model when SMB and HML are added.

Zhou (1996) explores how term structure of interest rates is linked to shifts in the equity market. It shows that interest rates, particularly at long horizons, significantly impact stock return. It also demonstrates how long-term real interest levels justify much of the dividend-price-ratio variability. This result confirms the belief that significant equity market volatility is related to strong long-term bond yield volatility.

Another study by Hahn and Lee (2006) examined how SMB and HML reflected variations in the market cycle. They offer an alternate three-factor model that forecasts return of 25 French and Fama portfolios, where two variables of the interest rate replace SMB and HML parameters. The proxies for systematic risk is change in term spread and change in default spread. These variables, along with market returns, reflect both the typical cross-section of return and the three-factor paradigm of Fama French. They also demonstrate that SMB and default spread shift follow an analogous systemic strategy, alongside size and HML, and term spread shift, alongside the book-to-market aspect, share a similar systemic trend. Their analysis thus follows the risk-oriented explanation of French-Fama factors.

4 RETURN PREDICTABILITY

Few pillars were established in the early empirical works of finance that were believed to be true. Such pillars, in particular, suggest that asset returns are volatile, prices vary tremendously, anticipated returns do not vary considerably over time, and finally, CAPM beta is a strong risk indicator and has an excellent explaining capacity for cross-sectional variability of stock returns. The new research generation has questioned such views in finance. The systemic risk calculation of CAPM beta is no longer sufficient, and many assets and approaches cannot explain their average returns by their market betas. Instead, multifactor models provide a better explanation of average return.

Moreover, asset returns are predictable. Statistical and economic results from recent empirical forecasting strategies support return predictability (Rapach & Zhou, 2012). A substantial amount of stock return variability is explained with variables such as dividend-price ratio, term spread. It mostly happens over long-horizon business cycles since it is still challenging to perform short-term stock return predictability. (Cochrane, 2005, pp. 389–390.)

4.1 Literature review on the prediction of return

Predictability of return is an exciting field in finance. Knowledge in this can increase yields for practitioners and help researchers build more practical asset price models that describe data better. Return predictability has one common misconception, which is, it contradicts the underlying requirements of an efficient market. According to the random walking models, potential stock return is uncertain, given currently available information. Nonetheless, forecast return do not interfere with market efficiency, since forecastability is compatible with exposure to macroeconomic risks, which varies over time. Therefore, when changes in systematic risk cause the variation of the predictive variable (return), then return can be predicted in an efficient market. (Suomala 2013.)

The most popular factor for predicting stock return is dividend-price ratio. Since dividend-price ratio varies over time, return may be forecasted. The work of Campbell and Shiller (1988) serves as the starting point for a most empirical study on dividend-price ratio and return relation. They claimed that when there is a reasonably high log dividend-price ratio, the dividend will rise more slowly in the future; future returns or a combination of the two are expected to be high. Therefore, as dividend-price ratios vary, dividend growth or growth in expected returns should be predicted. The common findings are that dividend-price ratio predicts return rather than potential growth in dividends. (Cochrane, 2007, 2011.)

Thus, predictable returns are dependent on trends of the economy's business cycle. The dividend-price ratio is correlated with the business cycle and other variables that forecast stock returns. Confirming Fama and French (1989), it shows projected returns differ across business cycles. When there is weak aggregate consumption and income, higher risk premiums or discount rates are needed during a period of an economic slowdown. When expected return goes up, price falls and vis versa. The variability in the discount rate and stock prices also contributes to changes in the dividend-price ratio. (Cochrane, 2005, p. 391 – 392.)

4.2 Methods for prediction of return

The return prediction is often studied in its simplest form using a predictive regression express as follows,

$$r_{t+1} = \alpha + \beta x_t + \varepsilon_{t+1} \quad (21)$$

Where x_t is a predictor variable, ε_{t+1} is the constant term, and r_{t+1} is the stock excess return. β , which is not yet established, is calculated using the data. The predictive power of the test variable x_t is evaluated using the OLS estimate of β , the R^2 value, or the t-statistics of β . According to the equation above, the variable x_t predicts excess return when $\beta \neq 0$. The equation makes use of information at time t in estimating the following period excess return. One limitation of this predictive regression model is when the disturbance term is serially correlated. It causes a bias in the t-statistics of β .

In order to solve the issue, the Newey and West standard errors are often used, which takes account of the disturbance term serial correlation and heteroskedasticity.

Because stock returns contain a significant, unpredictable component, this tends to make stock return predictability challenging. Only a small portion of the return is explained even with the best forecasting models. However, even less than 1% monthly R square is of economic significance. Models that explain a significant portion of returns fluctuation seem to have adjusted abnormal returns for risk, which is too good to be true. This is because the stock market, with lots of competition, poses challenges to develop a persistence model. When a good model is developed, other traders also implement it in their trading decision, which causes stocks to behave differently in ways that destroy the model's predictive power. When the model's predictive ability depends on exposure to aggregate risks, and the risk premium is continuously taken from the aggregate risk of varying times, the model tends to remain over time. (Suomala, 2013.)

4.3 Evidences that support the prediction of return

There are many literature in finance that studies dividend yield as a predictor variable of stock return. One such study is Ang and Bekaert (2007), which examines the predictability of dividend, cash flow, and excess stock return using dividend yield. They raised concerns about dividend yield long-run predictive power, claiming that dividend yield has no long-run predictive ability; instead, it can predict short-run stock return using the short-run interest rate. Furthermore, they claim a short interest rate rather than dividend yield produces the most robust predictability.

Evidences of stock return predictability using dividend yield is provided by Cochrane (2007). He took annual excess returns during the period 1926 – 2004 from the CRSP and regressed them. The results show a dividend yield to be significant statistically and economically and an excellent excess return predictor. The t-statistics are slightly above two, and therefore, the statistical significance is only marginal. On the other hand, Cochrane (2007) gives an economic significantly more substantial weight. The

regression result shows that the value of R square rises with time and that dividend yield is unable to predict future dividend growth.

A 1-year and 5-years time period return predictability regression is shown in Cochrane (2011). He regresses dividend yield against CRSP's annual excess return from 1947 – 2009. Even though the result is statistically significant, it is still not impressive. The coefficient of dividend yield in 1- year regression is 3.8, while that for 5-years is 20.6. In the five years, the value of R square often increases from 0.09 in one year to 0.28. The findings suggest that dividend yields predictive ability are of substantial economic value.

Cornell (2012) offers empirical evidence about the predictive ability of dividend yield, which is consistent with that of Cochrane (2007) and Cochrane (2011). He regresses dividend growth rate against annual return, and the result shows that dividend yields are statistically and financially forecasters of returns but do not provide any predictive ability for the estimation of dividend growth.

In addition to the dividend-price ratio that predicts stock returns, empirical work has identified many other factors. Valuation ratios, including term spread and default spread, associate with macroeconomic variables and, hence, correlate with expected business conditions (Campbell & Diebold, 2005). For example, book-to-market ratio, earnings-price ratio, nominal interest rates, consumption-wealth ratio, stock market volatility, and aggregate output are other predictor variables.

Stock return is estimated using default spread, dividend yield, term spread, T-Bill prices for one month, and industry lagging. The correlation between these variables and changes in the macroeconomic environment explains their predictive power. Default spread and dividend yield explain present economic situations as calculated by the recent growth of GDP and consumption, while future economic conditions are explained by term spread, shorter interest rate, and others. (Chen, 1991.)

A study by Jensen, Mercer, and Johnson (1996) investigated whether dividend yield, term spread and default spread help predict stock and bond returns. They also study

whether monetary policies influence these variables's explanations for the variability of stock and bond return. They claim variability in expected stock return is explained with dividend yield and default spread only during periods of expansive monetary policy. None of these variables seems to have significant explanatory power during a period of restrictive monetary policy. They also point out that term spread has no predictive ability at all.

In another study by Hjalmarsson, he used a large international dataset to study stock return predictability. The study covers equity returns from 40, including 24 established and 16 emerging markets. Short interest rate and term spread form the predictive factors, including dividend-price ratio and earnings-price ratio. His reports show little predictive potential for foreign data on dividend and earnings-price ratio. Instead, term spread and short interest rates exhibit strong robustness. For developed markets, the predictive value is greatest. (Hjalmarsson, 2009.)

5 PREDICTABILITY REGRESSIONS

This section outlines (1) my inspiration for the use of the chosen predictor variables, (2) description of the data used, and (3) the predictive regression result for one month in advance.

5.1 Selection of predictor variables employed

The predictive regression used for this investigation looks as follows,

$$\mathbf{ersf}_{t+1} = \beta_0 + \beta_1 \mathbf{pd} + \beta_2 \mathbf{ep} + \beta_3 \mathbf{vrp} + \beta_4 \mathbf{ts} + \beta_5 \mathbf{ltr} + \beta_6 \mathbf{infl}, \quad (22)$$

Where $\mathbf{ersf}_{t+1} = \log(R_{s,t+1}/R_{f,t+1})$ equals excess return. It's defined as the realized excess return in month $t + 1$ on stocks over the prevailing risk-free rate. From the equation $\log(R_{s,t+1}/R_{f,t+1})$, $R_{s,t+1}$ equals stock gross return, and it is estimated as S&P 500 stock market nominal return for one-month. Stock returns are continuously compounded and include dividends. $R_{f,t+1}$ equals gross risk-free rate, estimated using one-month nominal return on a Treasury Bill of three-months. The right side of the equation (30) contains predictor variables expressed in month t . Predictive results focus on the short-run, because there have been many criticisms about the empirical feasibility of such tests (Boudoukh, Richardson & Whitelaw, 2006; Bauer & Hamilton 2017).

This analysis uses two sets of predictor variables – stock market and interest rate related variables. The first set of stock related variables is the price-dividend ratio, earnings price ratio, and variance risk premium. The price-dividend ratio (**pd**) for the S&P 500 index is used as predictor variable. It represents the ratio between the index closing end-of-month nominal value and its past twelve months' cumulative dividend. Using U.S. data, **pd** shows a strong correlation with surplus consumption measures; hence, it is justifiable to add **pd** in the predictive regression to help explain excess return.

The earnings price ratio (**ep**) defines the ratio between the S&P 500 indexes' twelve months moving sum of earnings and its closing end-of-month nominal value. Several

studies have included this variable to understand the equity premium (e.g., Welch & Goyal, 2007).

The variance risk premium (**vrp**) defined the difference between volatility realized on S&P 500 index and implied volatility on option traded on S&P 500 index (Bollerslev, Tauchen, & Zhou, 2009). Much research has found a valuable explanation for excess returns for stocks from variance risk premium (e.g., Attanasio 1991; Guo, 2006; Welch & Goyal, 2007).

The next set of variables is the interest rate-related variables. Term Spread (**ts**) is obtained from the difference between return on long-run government security and Treasury bills. The other two interest rate-related variables are Long-term rate of return (**ltr**) and inflation rate, as used in Welch and Goyal (2007).

5.2 Data sources

Monthly data are used for empirical analysis from 2001.M7 to 2018.M12. The choice of dataset heavily depends on the availability of data relating to the chosen predictor variables. Nominal end-of-month data on the S&P 500 index, nominal earnings, nominal dividend, nominal risk-free rate, treasury bill rate, the yield on long-run government bonds, and inflation are taken from Amit Goyal personal website. $(P_t + D_t/12)/P_{t-1}$ to define the overall nominal return on S&P 500 index, where P_t is the closing end-of-month nominal value and D_t it's past twelve months cumulative dividend. In month t , the **pd** is defined as P_t/D_t and **ep** as E_t/P_t . Data on monthly **vrp** for the S&P 500 index is obtained from Hao Zhou's website.

The summary statistics for excess return and six predictor variables are presented in Table 1. It shows the average monthly excess return as 0.55% with a negative skewness and excess kurtosis. Excess return distributions show that it can go negative as much as -17.71% and positive as much as 11.44%. A close look at the six predictor variables shows that three of the six variables equally portray negative skewness and excess kurtosis (**pd**, **vrp**, and **infl**).

Next to the summary statistics is Table 2, which contain the correlation matrix for excess return and six predictor variables. Strongest correlation between variables is -0.32, and this is between **ts** and **ep**. The goal here is to include predictor variables that exhibit very little correlation with each other; therefore, their inclusion seems justifiable based on their correlation coefficients.

Table 1: Excess return and six variables summary statistics: 2001.M7 to 2018.M12

| Variable | Mean | St. Dev. | Skewness | Kurtosis | Min | Max |
|-------------|-------|----------|----------|----------|---------|-------|
| ersf | 0.55 | 4.20 | -0.70 | 1.50 | -17.71 | 11.44 |
| pd | 52.68 | 7.69 | -0.14 | 1.89 | 26.60 | 77.14 |
| ep | 0.05 | 0.01 | -0.83 | 0.64 | 0.01 | 0.08 |
| vrp | 12.53 | 22.34 | -4.71 | 53.47 | -218.56 | 80.61 |
| ts | 0.03 | 0.01 | -0.43 | -0.83 | -0.00 | 0.05 |
| ltr | 0.01 | 0.03 | 0.10 | 2.04 | -0.11 | 0.14 |
| infl | 0.00 | 0.00 | -0.83 | 3.52 | -0.02 | 0.01 |

Table 2: Excess return and six variables' correlation matrix

| | ersf | pd | ep | vrp | ts | ltr | infl |
|-------------|-------------|-----------|-----------|------------|-----------|------------|-------------|
| ersf | 1.00 | | | | | | |
| pd | -0.14 | 1.00 | | | | | |
| ep | 0.09 | 0.07 | 1.00 | | | | |
| vrp | 0.27 | 0.06 | -0.17 | 1.00 | | | |
| ts | 0.00 | -0.04 | -0.32 | 0.18 | 1.00 | | |
| ltr | 0.07 | -0.06 | 0.05 | 0.04 | -0.06 | 1.00 | |
| infl | 0.07 | 0.14 | 0.06 | 0.16 | -0.02 | -0.27 | 1.00 |

5.3 Predictive regression results

The predictive regression results are presented in Tables 3 through 5 and, Figures 1 through 6. Newey-West HAC corrected standard error compute t-statistic of the coefficients of the variables. Predictor variables with bold entries indicate they are significant at least at 5% level. Below every regression model is also the R^2 and adjusted R^2 .

Figures 1 through 6 presents a scatterplot for the different chosen predictor variables at time t against excess return in month $t+1$. Figure 1 shows price-dividend ratio versus excess return. It exhibits a negative slope indicating that the higher values of **pd** predict lower values of stock excess return. Figures 2 through 6 exhibits a positive regression line indicating that higher values of these predictor variables forecast higher value of stock excess returns. Significant findings cover the sample period without crisis, such as the 2008 and 2009 global financial crisis.

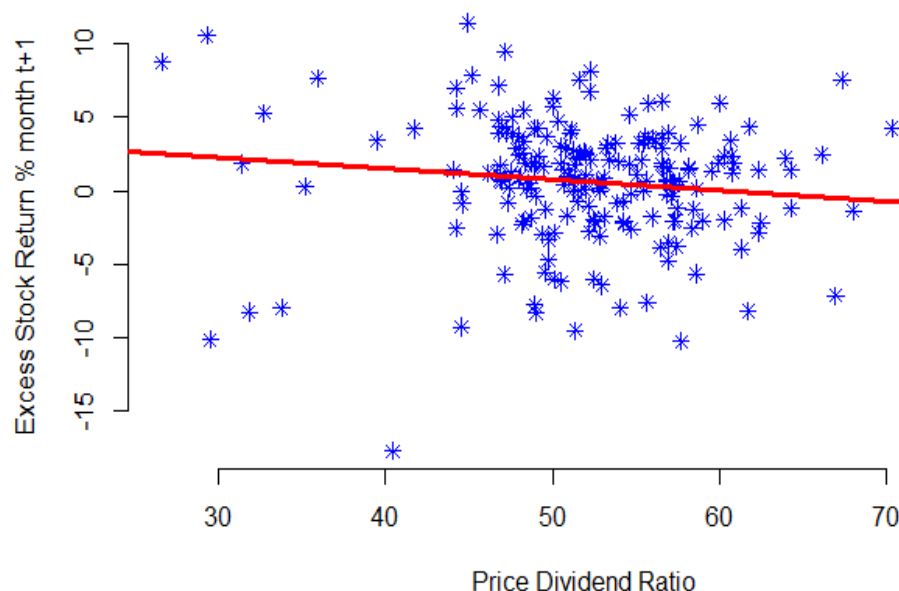


Figure 1: Price-dividend ratio versus one month in advance stocks excess return

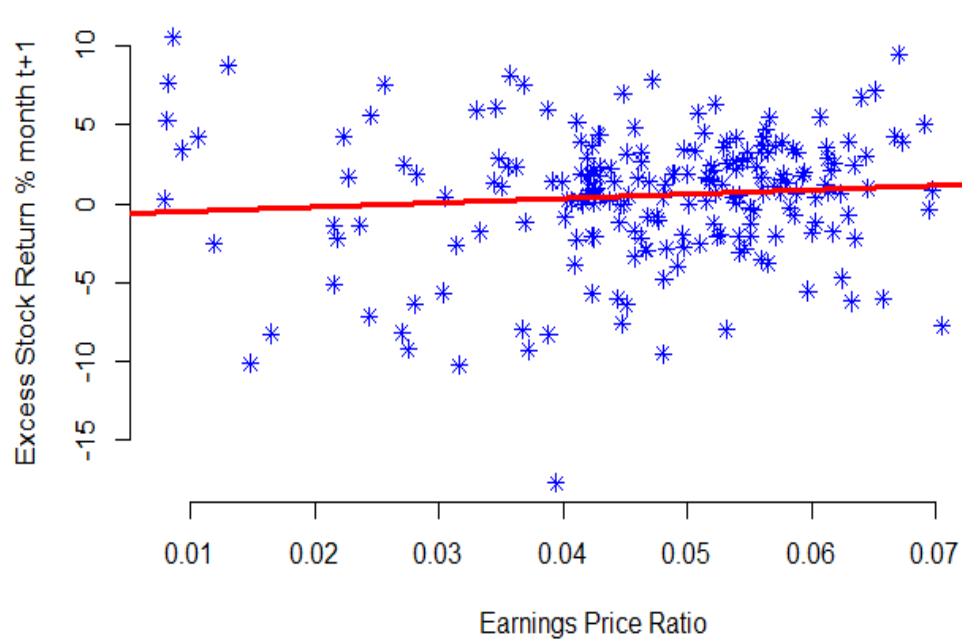


Figure 2: Earnings price ratio versus one month in advance stocks excess return

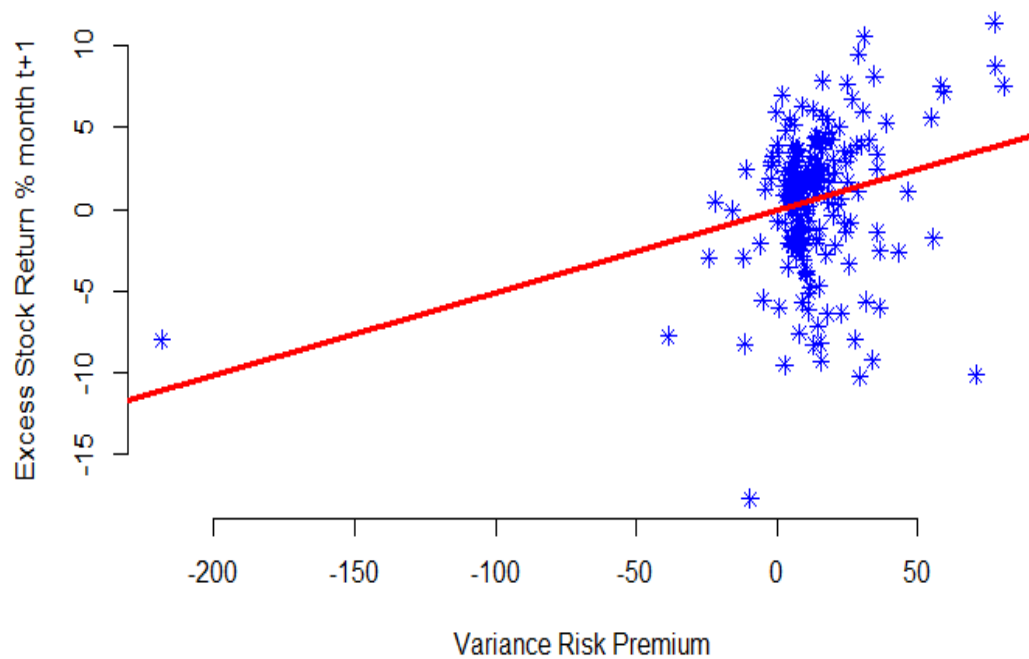


Figure 3: Variance risk premium versus one month in advance stocks excess return

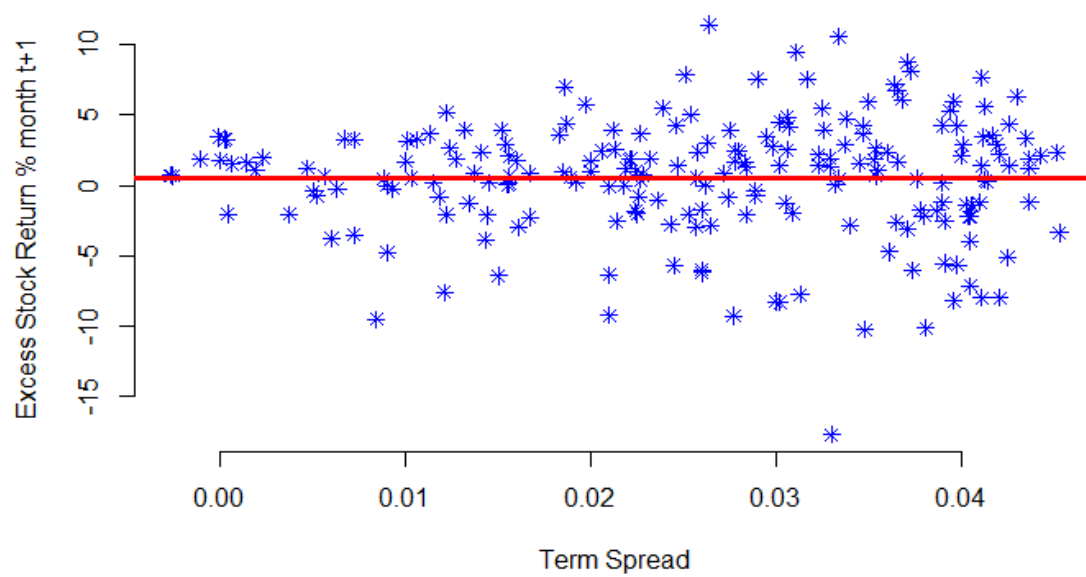


Figure 4: Term spread versus one month in advance stocks excess return



Figure 5: Long-term rate of return versus one month in advance stocks excess return

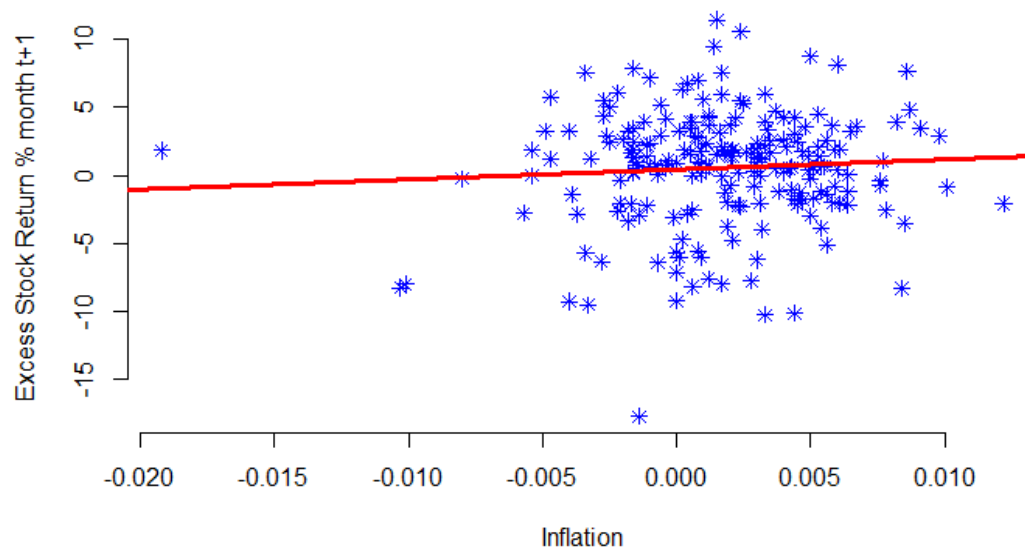


Figure 6: *Inflation versus one month in advance stocks excess return*

Table 3, contains full sample predictive results for the entire sample from 2001.M7 to 2018.M12. This table contains multiple regression models of different possible combinations of the predictor variables. Model 1 includes **pd**, **ep**, and **vrp**, which are stock market-related predictor variables. Irrespective of the regression model from 1 to 4, **pd** generate estimated coefficients, which are not only negative but also statistically significant. This robust finding is compatible with multiple previous reports, indicating a higher price-dividend ratio forecast a lower stock excess return. Unlike **pd**, **ep** shows a positive but also statistically significant coefficient, consistent with earlier research.

Vrp also has an estimated coefficient, which is positive, statistically significant, and consistent with past research work. Several literature has sighted variance risk premium as an indicator of macroeconomic instability. Therefore, it implies that an economic downturn in month t corresponds to higher excess return for investors in month $t+1$. Using only these three stock market-related predictor variables, model 1 produces an adjusted R-square statistic of 11%. It implies that 11% in the variation of excess return is explained by **pd**, **ep**, and **vrp**.

Model 2 in Table 2 shows the possible combination of the interest rate related predictor variables. Here, **ts**, **ltr**, and **infl** are put together. The estimated coefficient for each of the predictor variables is positive but statistically non-significant. The non-significance of these three variables show consistency across all possible regression models. It is also reflected in their adjusted R-square statistics of – 0%. It implies the three variables by no means explain any changes in stock excess return.

Model 3 form a possible combination of all the predictor variables (**pd**, **ep**, **vrp**, **ts**, **ltr**, and **infl**). As seen earlier, **pd**, **ep**, and **vrp** are statistically significant across all the different models while **ts**, **ltr**, and **infl** are not. The model generates an R-square statistic of 10%. Therefore, adding the interest rate related variables reduces the adjusted R-square from 11% to 10%. Model 4 has a possible combination of variables based on stepwise regression on Akaike information criteria (AIC). In this case, it is same as model 1 and can express as follows,

$$\text{ersf}_{t+1} = 2.29 - 0.09 \cdot \text{pd} + 48.28 \cdot \text{ep} + 0.06 \cdot \text{vrp}$$

Table 3: Predicting Excess Stock Return: Full Sample Results

| 2001.M7 – 2018.M12 | Model 1 | Model 2 | Model 3 | Model 4 |
|--------------------------|--------------------------|-------------------|--------------------------|--------------------------|
| Intercept | 2.29 (2.08) | 0.25 (0.69) | 2.48 (2.30) | 2.29 (2.08) |
| Price dividend ratio | -0.09* (0.04) | | -0.09* (0.04) | -0.09* (0.04) |
| Earnings price ratio | 48.28* (20.67) | | 45.24* (21.86) | 48.28* (20.67) |
| Variance risk premium | 0.06*** (0.01) | | 0.06*** (0.01) | 0.06*** (0.01) |
| Term spread | | 2.26 (23.33) | -2.75 (23.60) | |
| Long-term rate of return | | 12.45 (9.41) | 6.82 (9.02) | |
| Inflation rate | | 103.09 (77.79) | 54.19 (76.11) | |
| R ² | 0.12 | 0.01 | 0.12 | 0.12 |
| Adj. R ² | 0.11 | -0.00 | 0.10 | 0.11 |
| Num. obs. | 210 | 210 | 210 | 210 |
| RMSE | 3.97 | 4.20 | 3.99 | 3.97 |

The t- statistics are based on Newey-West heteroskedasticity, and autocorrelation corrected covariance matrices.

Tables 4 and 5 present the split-sample predictive regression results. There are two splits, and the first goes from 2001.M7 to 2010.M3, and the second goes from 2010.M4 to 2018.M12. One interesting thing about both splits is that the second split and full sample regression are similar except for the non-significance of **ep** coefficients and a higher adjusted R-square statistics. The first split does not seem different in many ways. Therefore, this supports the fact that the findings are robust to data not linked to the 2008 and 2009 global financial crises, which are in the first split.

The first split runs from 2001.M7 to 2010.M3, and it includes data for the 2008 and 2009 global financial crisis. The estimated coefficients for **pd**, **ep**, and **vrp** are almost exact for the full sample and the first split regressions. However, while **pd**, **ep**, and **vrp** are statistically significant in full sample, only **vrp** is significant in first split regression. The dilution of significance might result from reduced observations, giving rise to a lower adjusted R-square statistic. It is also essential to notice that Model 4, based on step-wise regression, has just **vrp** as a predictor variable.

Table 4: Predicting Excess Stock Return: First Split Sample Results

| 2001.M7 – 2010.M3 | Model 1 | Model 2 | Model 3 | Model 4 |
|--------------------------|-------------------------|--------------------|------------------------|------------------------|
| Intercept | 1.16 (2.54) | -0.59 (0.98) | -0.60 (3.21) | -0.39 (0.50) |
| Price dividend ratio | -0.07 (0.05) | | -0.07 (0.05) | |
| Earnings price ratio | 46.50 (33.50) | | 69.13 (46.05) | |
| Variance risk premium | 0.05** (0.02) | | 0.04* (0.02) | 0.04* (0.02) |
| Term spread | | 13.41 (30.26) | 37.48 (40.30) | |
| Long-term rate of return | | 17.92 (14.03) | 13.08 (13.88) | |
| Inflation rate | | 158.93 (105.86) | 76.00 (109.24) | |
| R ² | 0.09 | 0.03 | 0.10 | 0.06 |
| Adj. R ² | 0.06 | -0.00 | 0.05 | 0.05 |
| Num. obs. | 105 | 105 | 105 | 105 |
| RMSE | 4.52 | 4.66 | 4.55 | 4.54 |

The t- statistics are based on Newey-West heteroskedasticity and autocorrelation corrected covariance matrices

The second split sample runs from 2010.M4 to 2018.M12 without data for the 2008 and 2009 global financial crisis. The estimated coefficients here are similar to the full

sample and also statistically significant, except for **ep**, which gives a negative coefficient. It does not consider the interest rate-related predictors who are non-significant irrespective of the model or period. It is crucial to highlight, the second split sample reports a very high adjusted R-square statistic, which is more than twice that of the full sample. Model 4, which is the best model, has **pd** and **vrp** as predictor variables with an adjusted R-square statistic of 23%. It means that **pd** and **vrp** explain 23% in the variations of excess stock return in month $t+1$. It can be expressed as follows,

$$\text{ersf}_{t+1} = 16.75 - 0.34*\text{pd} + 0.11*\text{vrp}$$

Table 5: Predicting Excess Stock Return: Second Split Sample Results

| 2010.M4 – 2018.M12 | Model 1 | Model 2 | Model 3 | Model 4 |
|--------------------------|--------------------------|-------------------|--------------------------|--------------------------|
| Intercept | 17.48** (5.92) | 1.14 (1.09) | 17.37** (6.33) | 16.75** (5.48) |
| Price dividend ratio | -0.34** (0.11) | | -0.35** (0.12) | -0.34** (0.11) |
| Earnings price ratio | -12.53 (37.71) | | 17.02 (48.38) | |
| Variance risk premium | 0.11*** (0.03) | | 0.12*** (0.03) | 0.11*** (0.02) |
| Term spread | | -12.53 (41.29) | -53.22 (47.39) | |
| Long-term rate of return | | 7.81 (12.55) | 0.67 (11.41) | |
| Inflation rate | | 33.94 (124.48) | 159.55 (111.67) | |
| R ² | 0.24 | 0.00 | 0.27 | 0.24 |
| Adj. R ² | 0.22 | -0.02 | 0.22 | 0.23 |
| Num. obs. | 105 | 105 | 105 | 105 |
| RMSE | 3.24 | 3.72 | 3.24 | 3.23 |

The t- statistics are based on Newey-West heteroskedasticity and autocorrelation corrected covariance matrices. t-statistics are presented in parenthesis.

*** p < 0.001, ** p < 0.01, * p < 0.05

Results from the chosen predictor variables and the predictive regressions shows, interest rate-related predictor variables (**ts**, **ltr**, and **infl**) have a poor performance in explaining excess stock return. These variables are consistently statistically non-

significant across different models and sample periods. The stock market-related variables (**pd**, **ep**, and **vrp**) are good excess return predictors with **vrp** being a robust predictor. The **vrp** is consistently statistically significant across all the different models and sample periods. Moreover, considering the best models using the stepwise regression, the **vrp** is always present.

6 SUMMARY

Return predictability is one key area of financial economics that has evolved over the years. It has attracted an enormous amount of research with thousands of literature. Even with this development, there are still questions regarding what predictor variables are a robust predictor of excess stock return. Many empirical works have put forward several variables, which at some points are contradicted by other studies. It is partly because different scholars use different predicting techniques and data over different periods, which pose a significant challenge on generally acceptable predictor variables and return predictability. Most researchers address this issue by conducting sub-period regressions and rolling window regressions.

This research seeks explanation into the predictability of stock excess return in the U.S. market. It aims at determining whether the six chosen variables (price-dividend ratio, earnings price ratio, variance risk premium, term spread, long-term rate of return and inflation) are robust predictors of one-month in advance excess stock return in the U.S. I also limited predictability to in-sample and over a shorter horizon.

The empirical result shows that all the stock market-related predictor variables – price-dividend ratio, earnings price ratio, and variance risk premium – are predictors of excess stock return in the U.S. market. Among these variables, the variance risk premium is the only robust predictor variable across different sub-periods and models. The statistical significance for price-dividend ratio and earnings price ratio varies across sub-period. The results show the predicting ability of price-dividend ratio is strongest in full sample and second split regression, while being statistically not significant for the first split. The earnings price ratio also show a strong statistical significance in full sample and non-significance in first and second split regressions. The findings are focus on the second split sample, which does not include data from the global financial crisis of 2008 and 2009. Regression result for the best model based on the stepwise regression show that the price-dividend ratio and variance risk premium can only explain 23% of one-month in advance excess stock return in the U.S. It also implies there are other variables in addition to these two that predict a one-month excess return.

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